Machine Learning for prognostics and optimization of particle accelerators

Machine Learning at Spallation Neutron Source (SNS), Oak Ridge National Lab (ORNL)

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Outline

- Overview of Machine Learning at SNS for Prognostics and Optimization
  - Infrastructure
  - Beam Loss Optimization
  - Target System Anomaly Reporting and Feedback
  - **Errant Beam Prediction using Machine Learning**
    - **Sensors and Data Collection**
    - **Data Curation**
    - **Beam Configuration and drift in the data**
    - **Conditional ML Models**
    - **Continual Learning and UQ**
- Conclusion, Future Direction, and References

Overview

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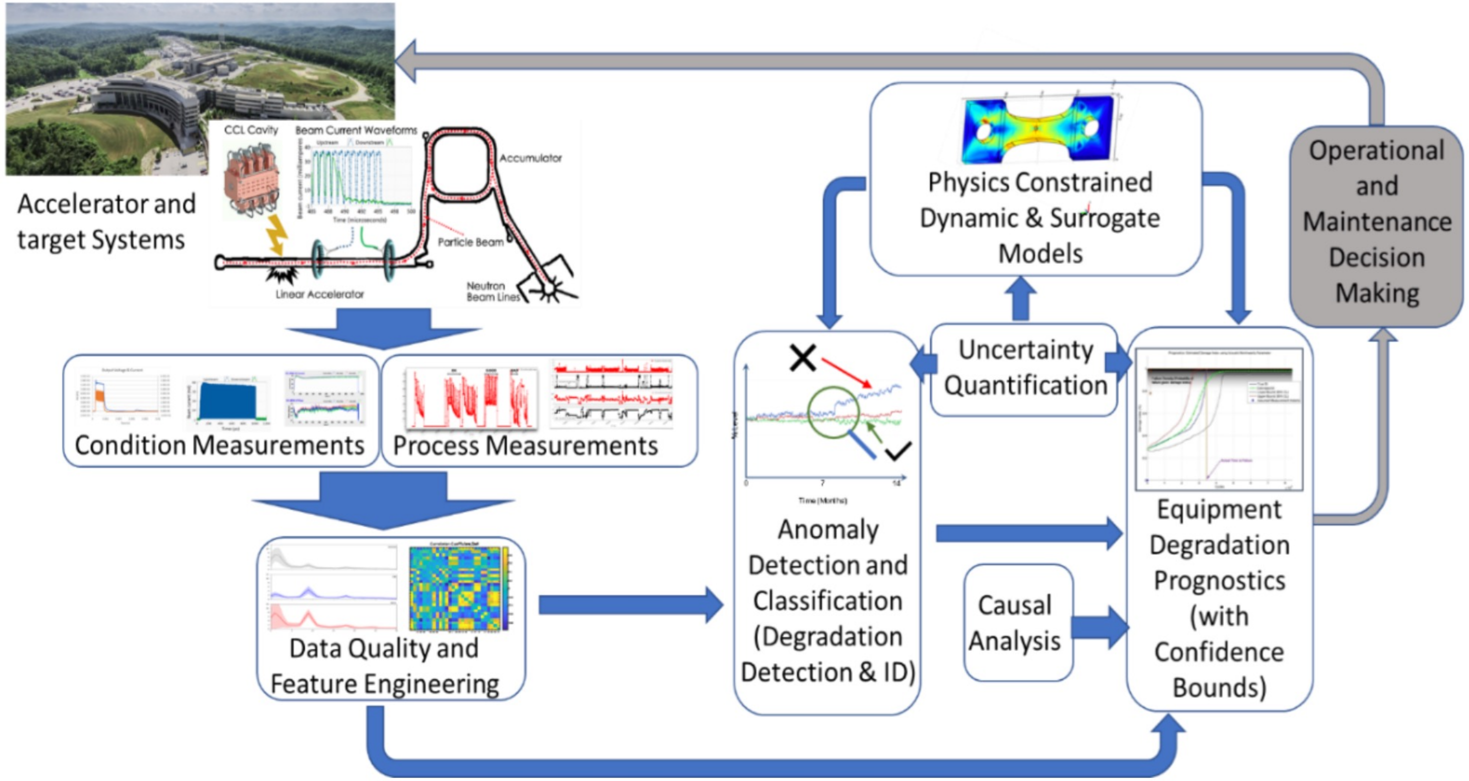
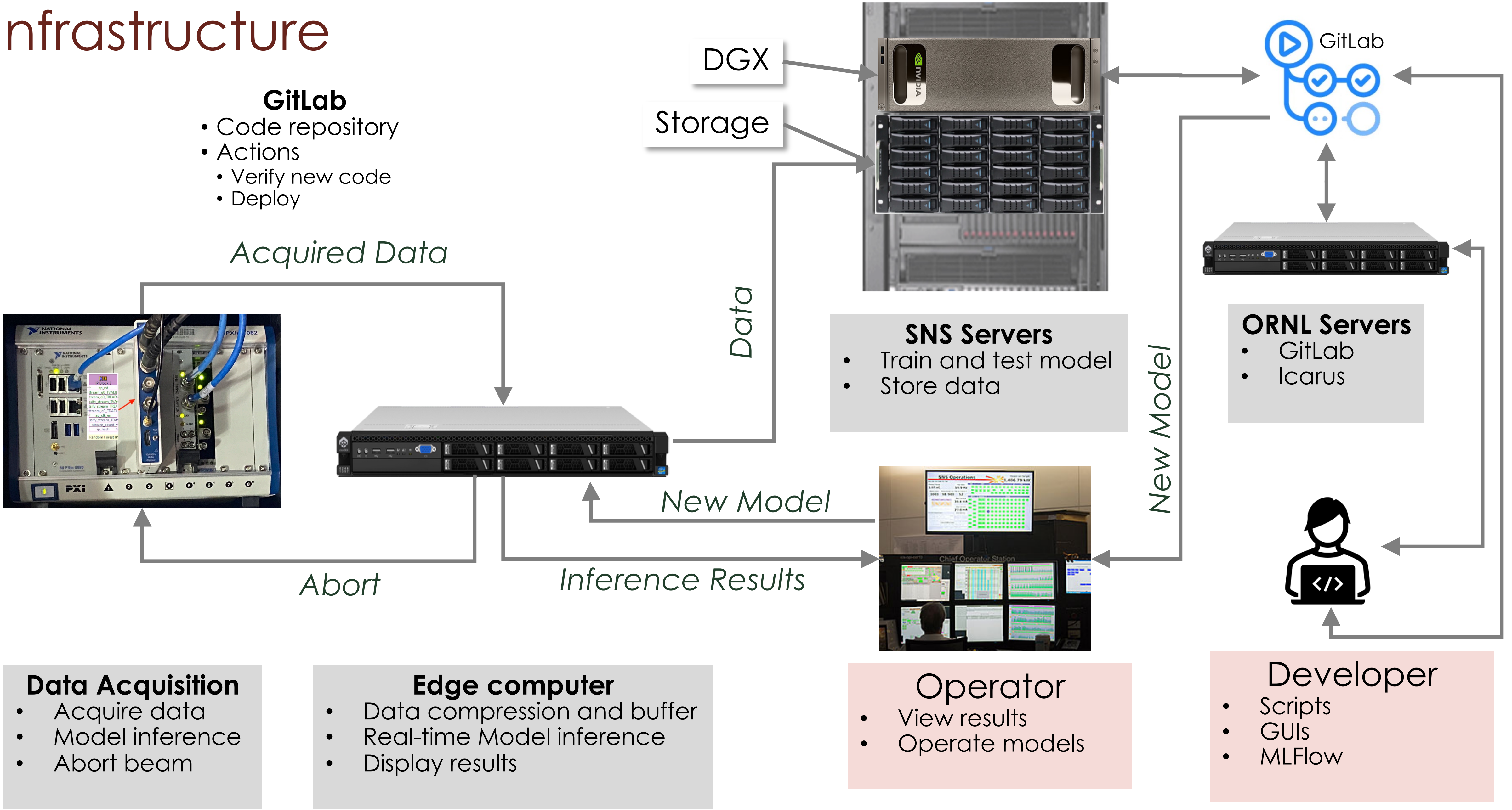
- Spallation Neutron Source (SNS) accelerator at Oak Ridge National Lab delivers 1.4 MW of a 1 GeV pulsed beam at 60 Hz (1.3 MW of 2.8 GeV after recent upgrade)
- Ongoing work on anomaly prediction, reporting and feedback system for **errant beams** and target systems using Machine Learning (ML) algorithms to reduce downtime
- ML based controls algorithms are being explored for beam loss tuning optimization
- Infrastructures to support long term ML lifecycles deployment are being developed



Infrastructure



Beam loss Optimization

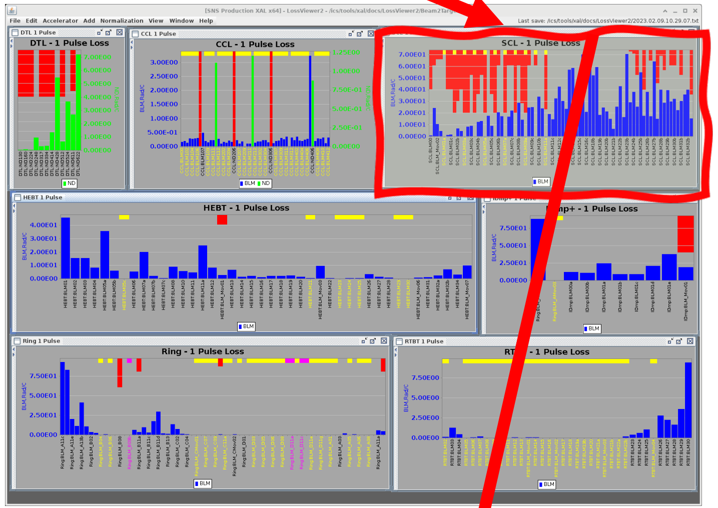
Goal: Reduce beam losses

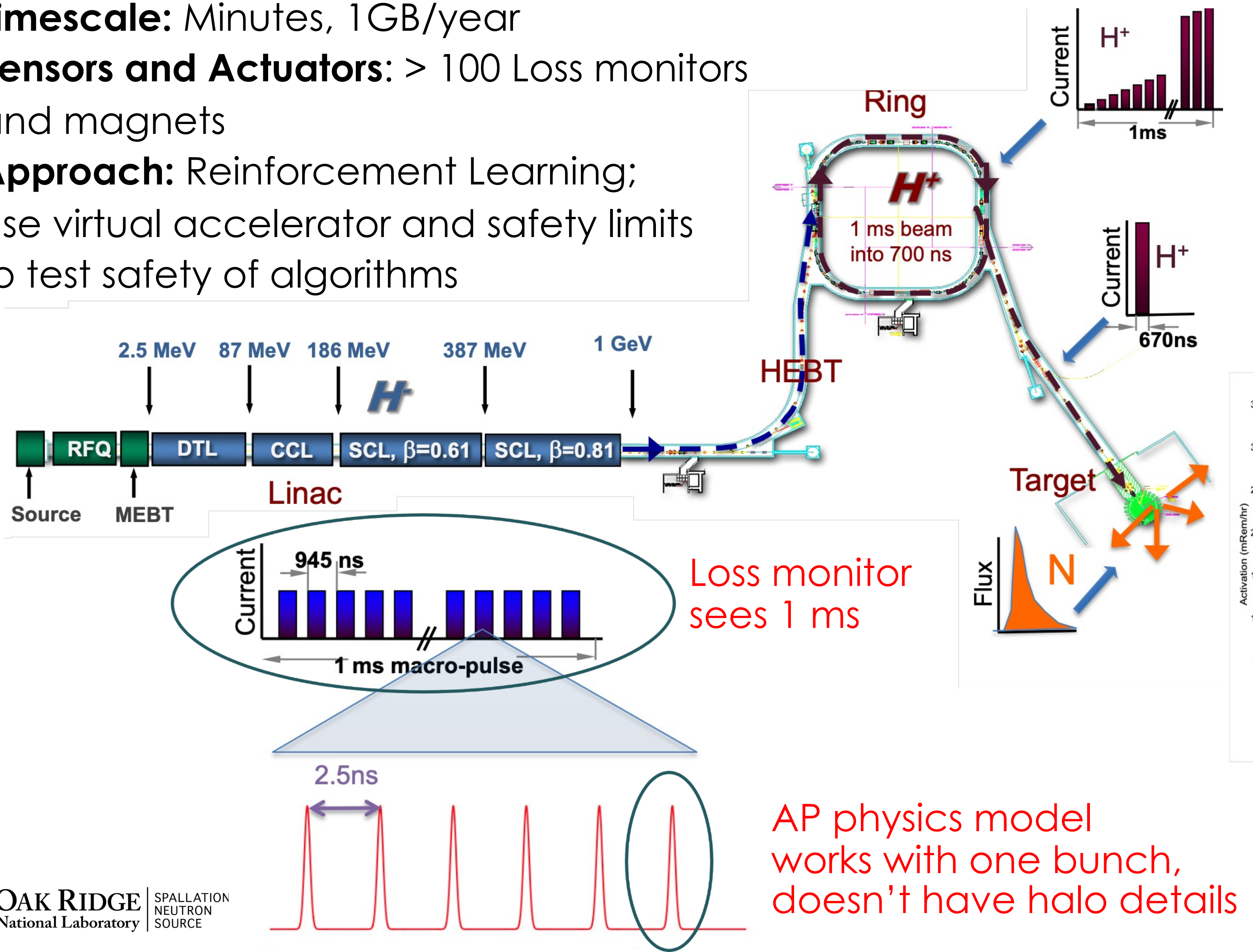
Timescale: Minutes, 1GB/year

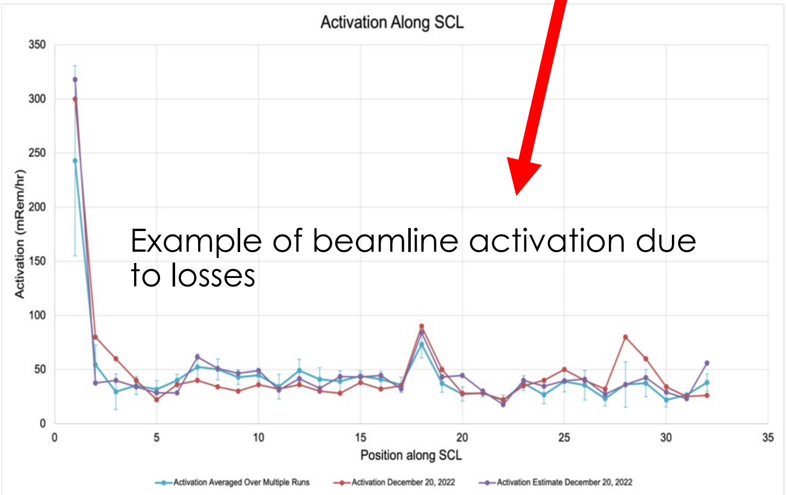
Sensors and Actuators: > 100 Loss monitors and magnets

Approach: Reinforcement Learning; Use virtual accelerator and safety limits to test safety of algorithms

Measured beam losses lead to activation







Talk - **From Physics Study to Operations by Carrie Elliott**

Target System Anomaly Prediction

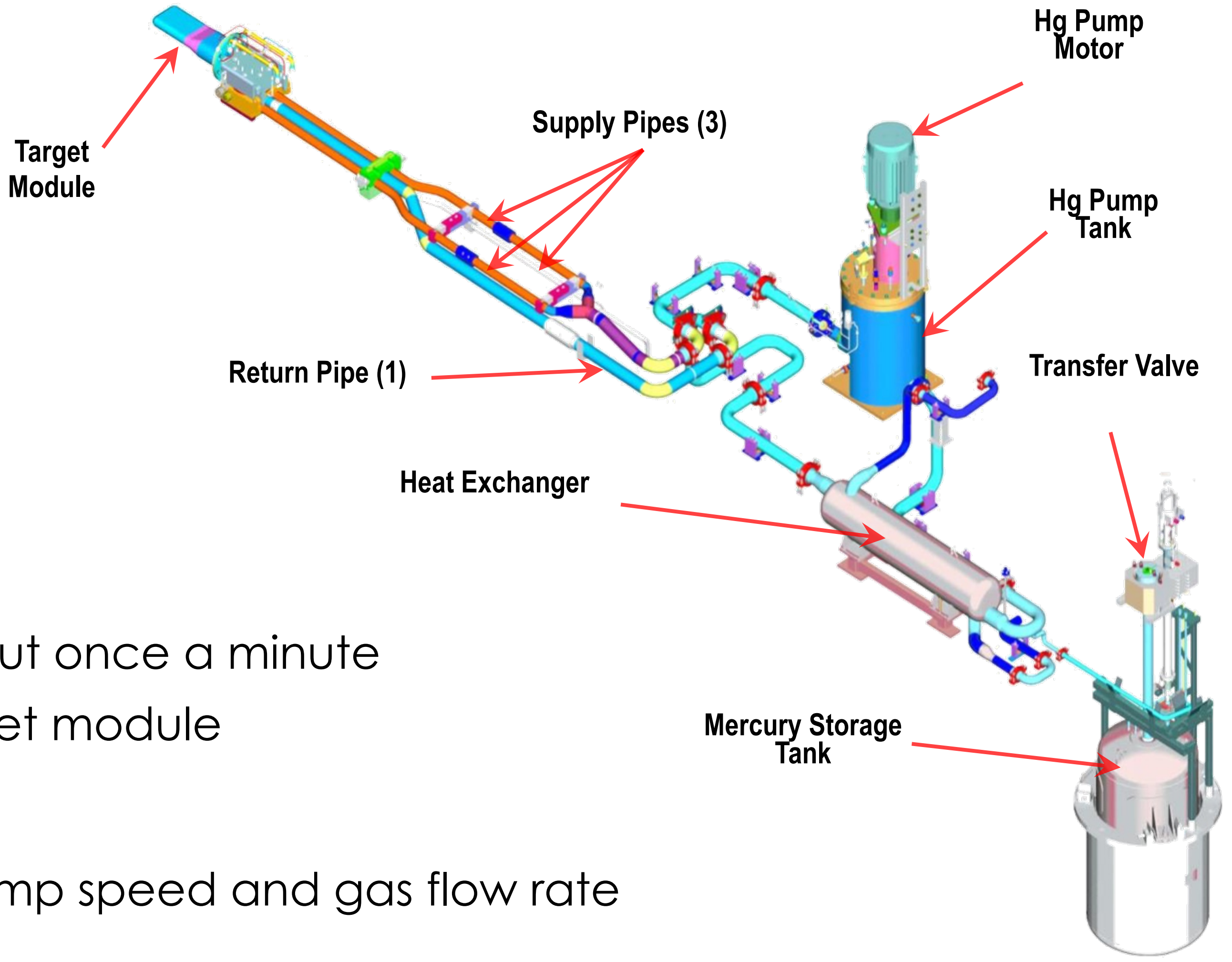
Goal: Reduce downtime due to target

Timescale: Minutes

Sensors and Actuators: Flow, Pressure, Temperature and PID controllers' valve and motors

Approach: Use archived and real-time data to train for anomalies, generate reports and alert for anomalies

- Operates with ~1400 L of liquid mercury
  - ~20 tons of mercury
  - Mercury circulates through the loop about once a minute
  - 4 slpm of helium gas injected at the target module
- Set it and forget it
  - Loop is intended to run at a constant pump speed and gas flow rate



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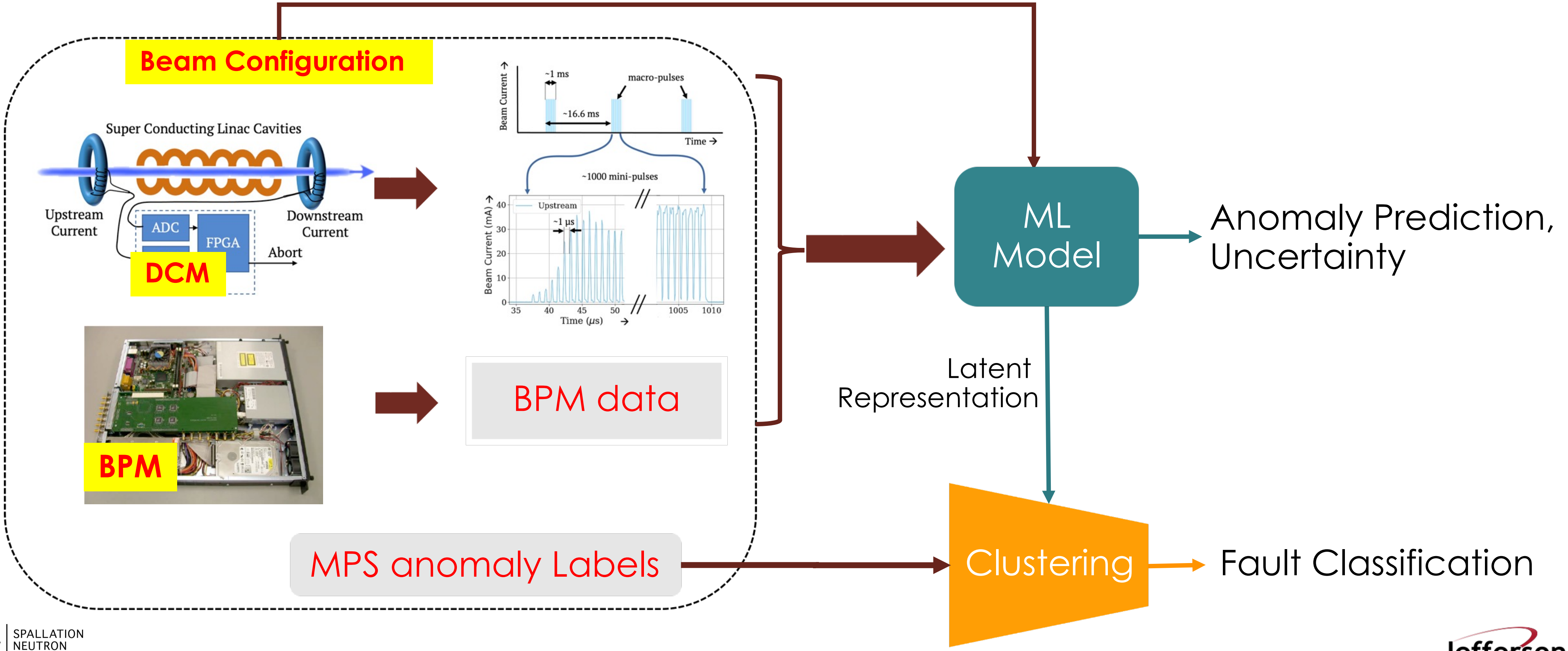
Errant Beam Prediction

Goal: Predict and prevent Errant beam pulses

Timescales: µsecs to 15 ms, stream: +100Mb/s

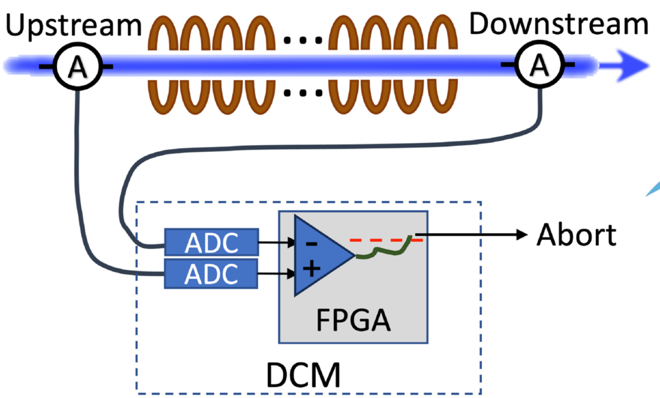
Sensors and Actuators: 1x Current Monitor and 30+ Beam Position Monitors

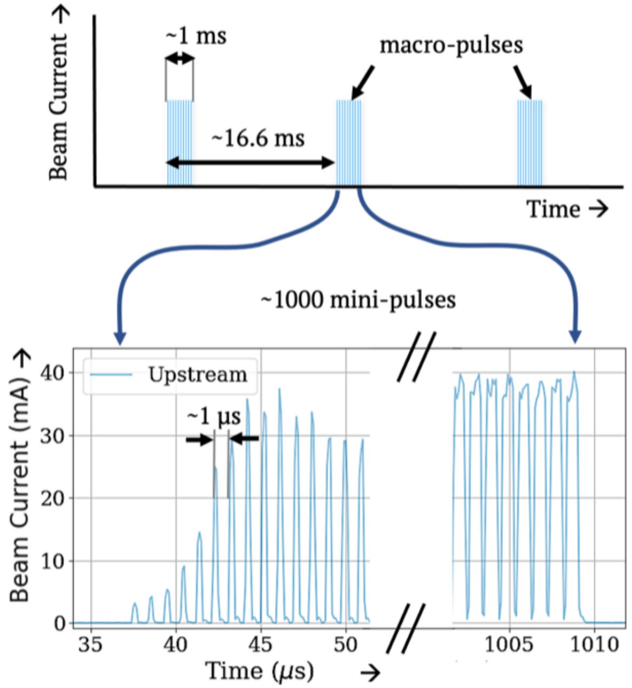
Approach: Use continual learning ML (Siamese and VAE) models to detect precursor and abort beam (FP must be very low <0.2%)



Sensors and Data Collection

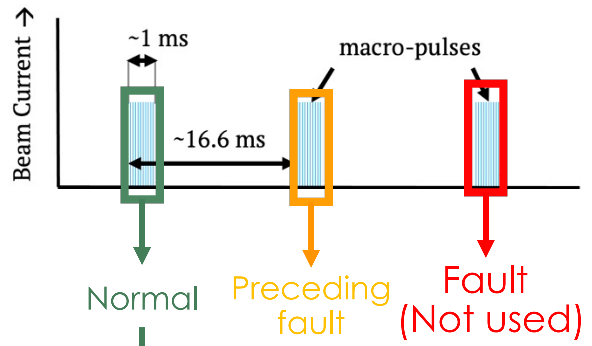
- SNS employs a DCM to protect the Super Conducting Linac (SCL)
- Continuously monitors upstream and downstream beam current waveforms to detect any loss
- FPGA and dedicated communication line with Machine Protection System (MPS)
- **DCM can be programmed to store all the beam current waveforms**
- Previous studies showed precursors are present in pre-fault data to indicate upcoming fault
- In addition, beam configuration settings are also store associated with these waveforms
- We are also looking into possibility of using Beam Position Monitor (BPM) data together with DCM data to improve the accuracy further





Data Curation

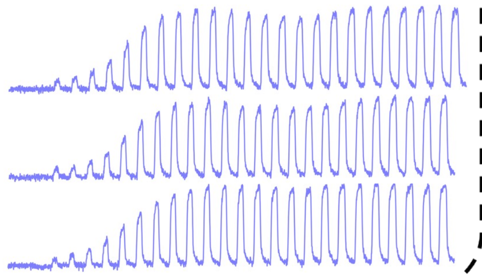
- Pre-cursors in the normal (pre-fault) beam current data
- Enables prediction of faults (Prediction not detection!)
- Label normal data immediately before fault as 1
- All other normal data instances labeled as 0



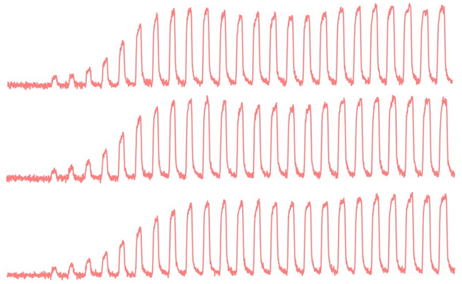
Marked as anomaly in training data

Marked as normal (including all the preceding samples until previous fault)

Reference Normal Pulses

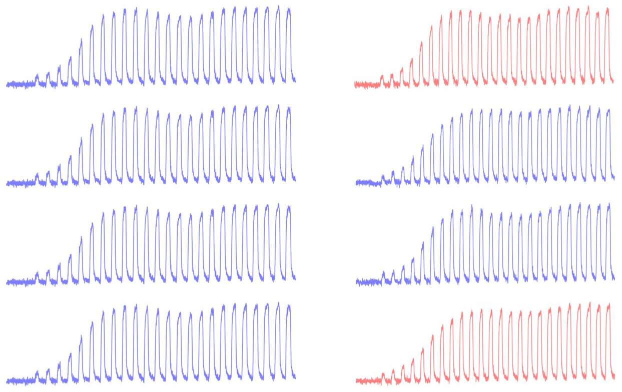


Pre-fault Pulses



Input to Siamese Model

Different Combinations of Normal to Normal (labeled 0) and Normal to "Before" pulses (labeled 1)

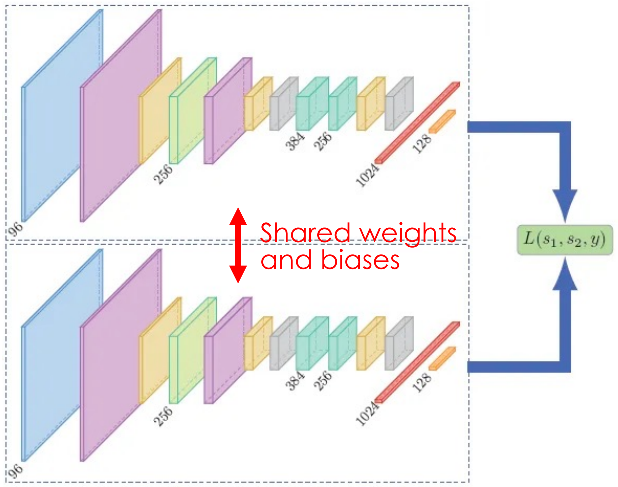


1

0

0

1

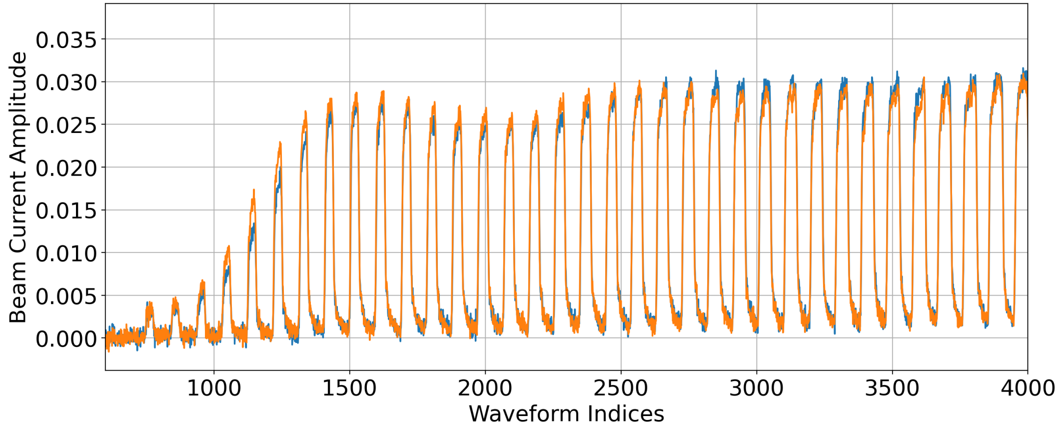


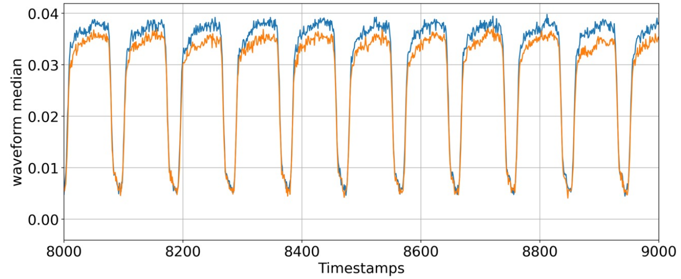
Siamese Model

Data Drift

Drift due to measurable parameters

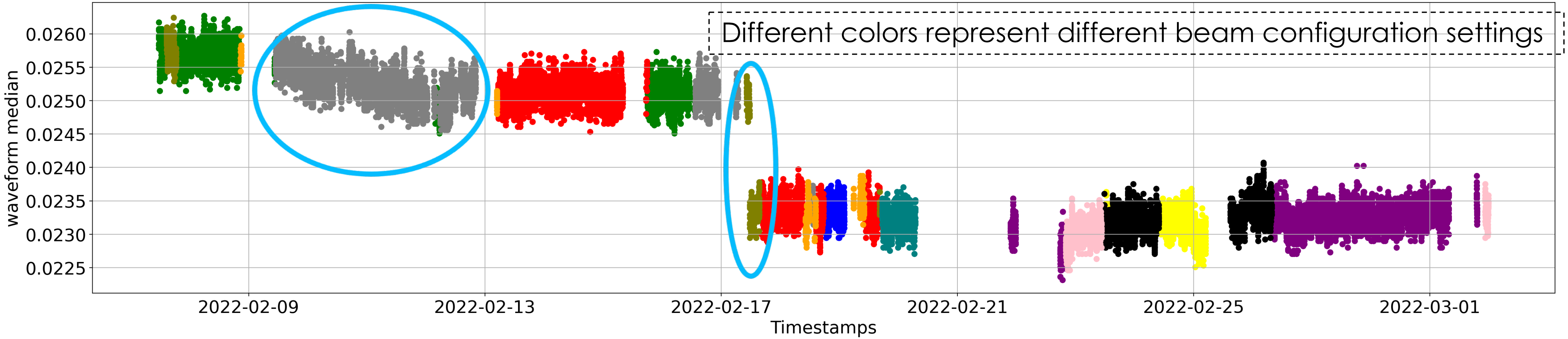
- Beam configuration are tuned continuously
- Changes in the config parameter → changes distribution of the beam current waveforms





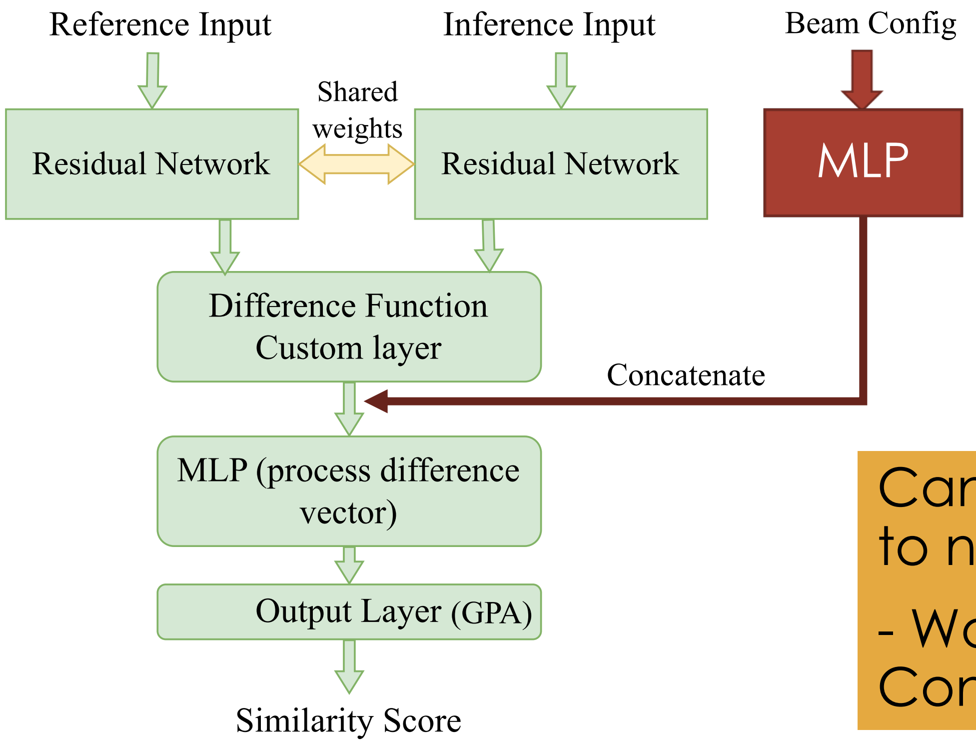
Drift due to non-measurable parameters

- Machine degradation, aging, maintenance, Equipment replacement etc. cause data distribution to change



ML Models

- Similarity based models can correctly classify unseen anomalies. Ex Siamese model, AE, VAE etc.
- Siamese Neural Network (SNN), and VAE to predict anomalies
- SNN learns twin embedding models to transform inputs into a latent space
- Distance measures are applied at latent space to compute the similarity



Do we account for drifts due to known parameters?

- Beam configurations as Conditional input
- Conditional SNN (CSNN) and Conditional VAE (CVAE)
- Potentially learn any cross-correlations between beam current data from different configs

Can the model adapt to distribution drifts due to non-measurable parameters?

- Work in progress to leverage developments in Continual Learning domain

Results

Evaluation Metric

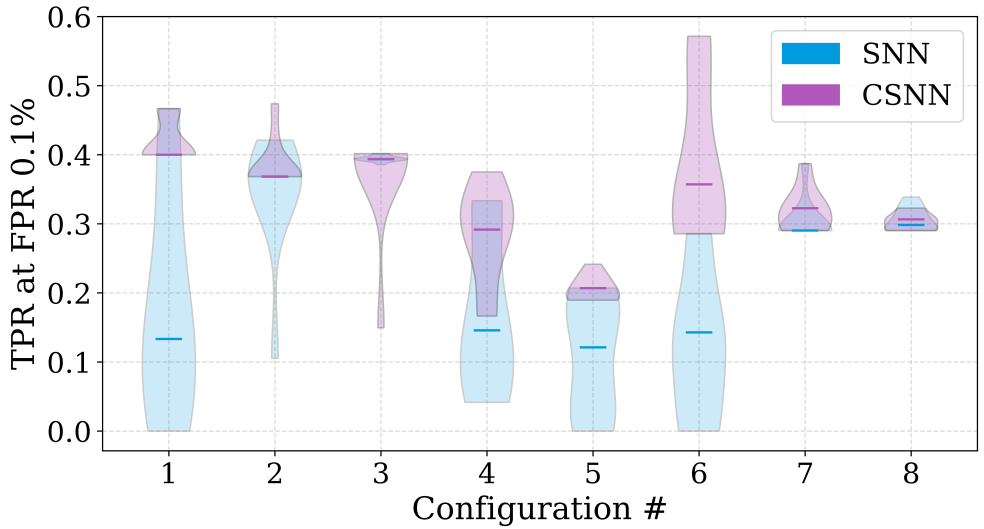
- Total downtime should not be increased by false alarms
- Maximum number of possible anomalies should be predicted before they occur
- Goal: Maximize True Positive Rate (TPR) while keeping False Positive Rate (FPR) below 0.1%

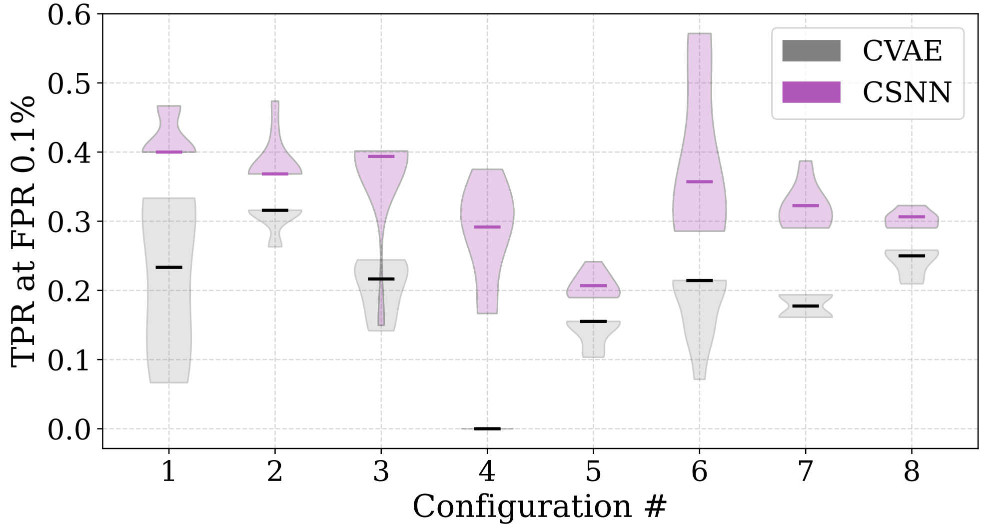
CSNN vs CVAE vs SNN

- Model architectures were selected after a HPO and NAS
- 10 Trials to provide statistically robust comparison
- CSNN outperforms both SNN and CVAE
- CVAE has 10 times more learnable parameters than CSNN

Inference Time

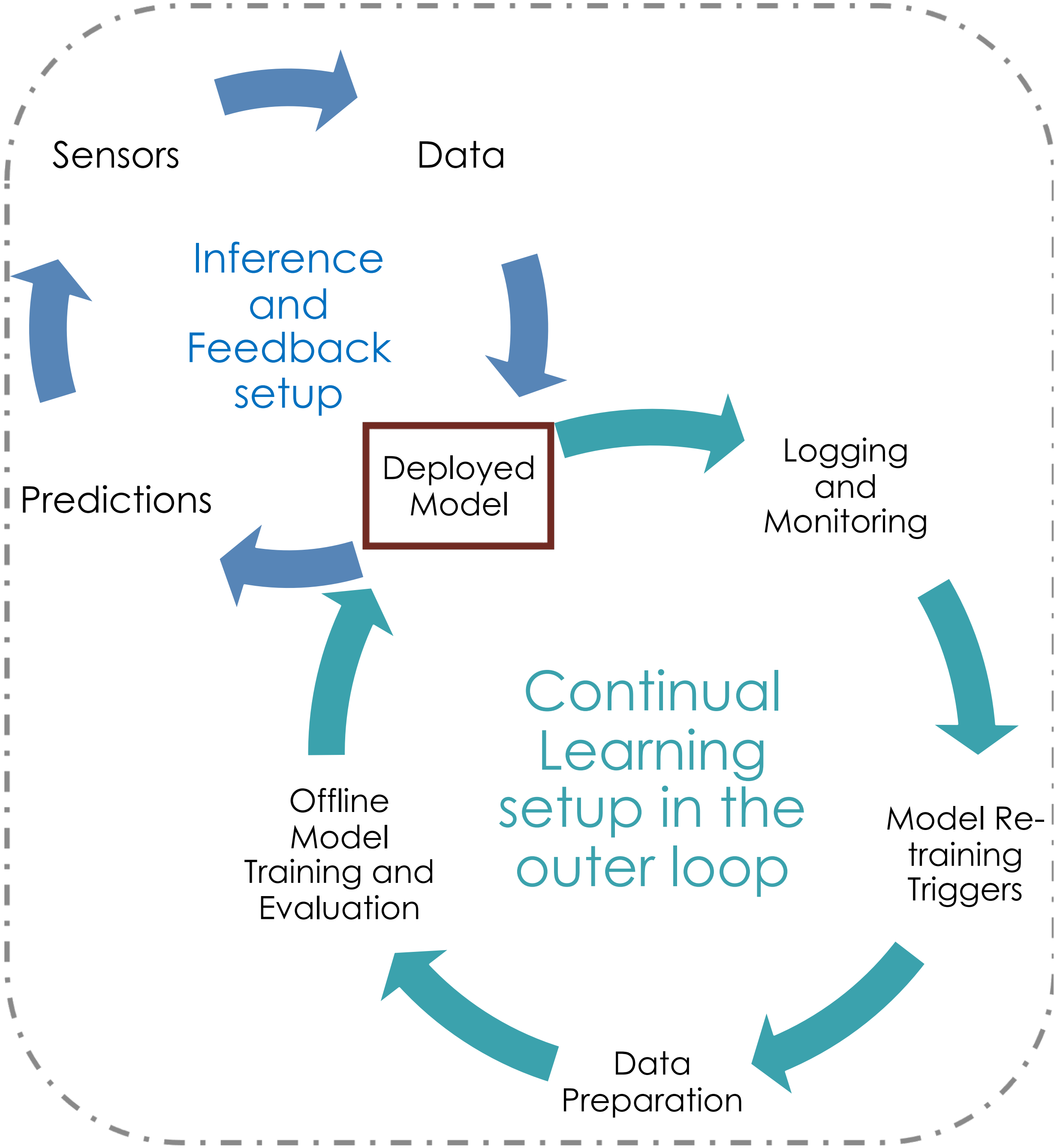
Intel CPU (Mark Rating)	Inference Time in ms (Deterministic/Uncertainty) SNN	CSNN	CVAE
Core i9-9880H (14235)	9.3/11.1	9.5/11.4	18.9/NA
Xeon E5-2618 (10881)	12.2/14.5	12.4/14.9	24.7/NA
Xeon W-2245 (19474)	**6.8/8.1**	**6.9/8.3**	**13.8/NA**





Continual Learning

- Model performance degrades when data distribution changes
- Defining Triggers for model re-training is challenging
- Sudden drifts due to config changes → include new config data in training set
- Gradual drifts due to non-measurable parameters → Continual Learning
- Model performance based triggers are most valued
- When aborted – no information whether it was right!
- Uncertainty Quantification can help defining re-training triggers
  - Distance aware uncertainty goes up → Model is less confident as data is **out of distribution**
- Catastrophic forgetting is a big issue to address



Conclusion

- Machine Learning is being deployed at SNS accelerator for anomaly prediction and optimization
- Conditional Siamese Models and Conditional VAEs are deployed to predict errant beams
- Beam Current Waveforms are used to predict upcoming anomalies
- Conditional Siamese Model outperforms
  a) Conditional VAE Siamese Models
  b) Siamese model trained on single beam configuration data
- Data drifts due to both measurable (beam config) and non-measurable (machine degradation, equipment replacement etc.) parameters
- Model performance degrades when data drifts
- Continual Learning is being explored to tackle data drifts

Open to Collaboration

Principle Investigators

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Use case lead

Anomaly Prediction and Continual Learning

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